Calhoun: The NPS Institutional Archive

DSpace Repository

Theses and Dissertations | 1. Thesis and Dissertation Collection, all items

2016-03

Using social media activity to identify personality characteristics of Navy personnel

Ward, Leslie

Monterey, California: Naval Postgraduate School

http://hdl.handle.net/10945/48492

This publication is a work of the U.S. Government as defined in Title 17, United States Code, Section 101. Copyright protection is not available for this work in the United States.

Downloaded from NPS Archive: Calhoun

http://www.nps.edu/library

Calhoun is the Naval Postgraduate School's public access digital repository for research materials and institutional publications created by the NPS community. Calhoun is named for Professor of Mathematics Guy K. Calhoun, NPS's first appointed -- and published -- scholarly author.

Dudley Knox Library / Naval Postgraduate School
411 Dyer Road / 1 University Circle
Monterey, California USA 93943

NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

THESIS

USING SOCIAL MEDIA ACTIVITY TO IDENTIFY PERSONALITY CHARACTERISTICS OF NAVY PERSONNEL

by

Leslie Ward

March 2016

Thesis Co-Advisors: Man-Tak Shing
Thomas Otani

Approved for public release; distribution is unlimited

THIS PAGE INTENTIONALLY LEFT BLANK

REPORT DOCUMENTATION PAGE

Form Approved OMB No. 0704–0188

Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instruction, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden to Washington headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202–4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188) Washington DC 20503.

1. AGENCY USE ONLY *(Leave Blank)*	2. REPORT DATE	3. REPORT TYPE AND DATES COVERED
	March 2016	Master's Thesis 03-31-2014 to 03-25-2016

4. TITLE AND SUBTITLE

USING SOCIAL MEDIA ACTIVITY TO IDENTIFY PERSONALITY CHARACTERISTICS OF NAVY PERSONNEL

5. FUNDING NUMBERS

6. AUTHOR(S)

Leslie Ward

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)

Naval Postgraduate School
Monterey, CA 93943

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)

N/A

10. SPONSORING / MONITORING AGENCY REPORT NUMBER

11. SUPPLEMENTARY NOTES

The views expressed in this document are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government. IRB Protocol Number: N/A.

12a. DISTRIBUTION / AVAILABILITY STATEMENT

Approved for public release; distribution is unlimited

12b. DISTRIBUTION CODE

13. ABSTRACT *(maximum 200 words)*

This research explores the use of Twitter to determine if the personality characteristics of well-performing Navy personnel can be identified based on their Twitter use. Well-performing Navy personnel are identified by using the publicly-available Navy promotion lists and then those names were used to query Twitter in order to identify possible accounts belonging to these Sailors. Data from those Twitter accounts that could be positively identified as belonging to Navy personnel were then fed into textual analysis software and each user's level of the personality traits in the Five Factor Model of personality was calculated based on the results previous research. These results and other data were also stored in a graph database in order to make the data easier to query.

Although this research shows that it is possible to successfully calculate a user's personality based on textual analysis of their Twitter activity, the primary conclusions of this research is that this method is insufficient to identify specific traits that make Navy personnel stand out on Twitter.

14. SUBJECT TERMS

Twitter, personality, Five Factor Model, graph database, textual analysis, LIWC

15. NUMBER OF PAGES 67

16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
Unclassified	Unclassified	Unclassified	UU

NSN 7540-01-280-5500

Standard Form 298 (Rev. 2–89)
Prescribed by ANSI Std. 239–18

THIS PAGE INTENTIONALLY LEFT BLANK

Approved for public release; distribution is unlimited

USING SOCIAL MEDIA ACTIVITY TO IDENTIFY PERSONALITY CHARACTERISTICS OF NAVY PERSONNEL

Leslie Ward
Lieutenant, United States Navy
B.S., Texas A&M University, 2005

Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN COMPUTER SCIENCE

from the

NAVAL POSTGRADUATE SCHOOL
March 2016

Approved by: Man-Tak Shing
Thesis Co-Advisor

Thomas Otani
Thesis Co-Advisor

Peter Denning
Chair, Department of Computer Science

THIS PAGE INTENTIONALLY LEFT BLANK

ABSTRACT

This research explores the use of Twitter to determine if the personality characteristics of well-performing Navy personnel can be identified based on their Twitter use. Well-performing Navy personnel are identified by using the publicly-available Navy promotion lists and then those names were used to query Twitter in order to identify possible accounts belonging to these Sailors. Data from those Twitter accounts that could be positively identified as belonging to Navy personnel were then fed into textual analysis software and each user's level of the personality traits in the Five Factor Model of personality was calculated based on the results previous research. These results and other data were also stored in a graph database in order to make the data easier to query.

Although this research shows that it is possible to successfully calculate a user's personality based on textual analysis of their Twitter activity, the primary conclusions of this research is that this method is insufficient to identify specific traits that make Navy personnel stand out on Twitter.

THIS PAGE INTENTIONALLY LEFT BLANK

Table of Contents

List of Figures

THIS PAGE INTENTIONALLY LEFT BLANK

List of Tables

THIS PAGE INTENTIONALLY LEFT BLANK

List of Acronyms and Abbreviations

API Application Programming Interface

BUPERS Bureau of Personnel

CSV Comma Separated Values

HTML Hypertext Markup Language

JSON JavaScript Object Notation

LIWC Linguistic Inquiry and Word Count

NoSQL Non-Structured Query Language

RDBMS Relational Database Management System

SQL Structured Query Language

TAPAS Tailored Adaptable Personality Assessment System

USN United States Navy

THIS PAGE INTENTIONALLY LEFT BLANK

Acknowledgments

Special thanks to my thesis advisors, Man-Tak Shing and Thomas Otani. When I came to Dr. Shing with my idea for a thesis, he was enthusiastic in helping me figure out how to make it a viable research idea and he guided me through the entire process. Dr. Otani stepped up at the last minute to be my co-advisor and answered every question that I asked him.

I would also like to thank Michael Atkinson of the NPS Operations Research Department, who walked me through the construction and use of the linear regression model that served as the basis for my calculations.

The initial idea for my thesis came from my work with the Chief of Naval Operations Strategic Studies Group and the idea to use social media profiles for recruitment was introduced and championed by CAPT Reggie Howard.

Thanks to LT Patrick Gillen, whose work with Twitter to identify OPSEC violations first inspired me to look at social media and who provided me with invaluable guidance for identifying Navy Twitter accounts and working with the Twitter API.

Thanks to LT Brian Crawford, who served as my sounding board to discuss problems and to listen to my rants when things weren't going well.

Last, but certainly not least, thanks to my family. My mother first introduced me to computer science and showed me how much fun programming is, which changed the course of my life. Both of my parents were always enthusiastic and interested to hear about what I was doing in my thesis and what I was learning in my classes. I appreciate my brothers and sister for not only giving me nieces and nephews, but also for being willing to drop everything and come see me whenever I make it back to Texas for a visit.

THIS PAGE INTENTIONALLY LEFT BLANK

CHAPTER 1:
Introduction

Nearly 65% of Americans use social media, according to the 2015 survey by Pew Research Center; in the 18–29 age range typically targeted for military recruitment, the number jumps to 90% [1]. The list of social media platforms is constantly growing. The most commonly used platforms are YouTube, Facebook, Google+, and Twitter; others include LinkedIn, Tumblr, Instagram, and Pinterest [2]. Social media is the third most common entertainment choice for Americans aged 16–24, behind television and hanging out [2]. People use social media to interact with friends, family members and celebrities. They post about the big events and little events in their lives. They provide their opinions on politics, world news, movies and TV, and sports. Americans spend an average of nearly two hours a day on social media; for 16–35 year-olds, that number is even higher [3].

Most social media platforms have the right, as laid out in their Terms of Service, to provide users' data to third-party sources, typically marketing firms. These third-party companies use data mining tools to identify targets for advertising and to determine trends, because there is so much useful information in a user's data. For example, LinkedIn has marketed its platform as a tool for both employers to find candidates with specific skills and for job-seekers to find employment.

1.1 Motivation

The U.S. Navy has a recruitment goal of 37,000 new active duty members in 2016 [4]. The current Navy recruiting process has multiple ways to identify potential new recruits; the process is known as *prospecting*. Recruiters visit schools, malls, parks, sporting events and unemployment offices to seek new prospects; recruiters attend 32,000 high schools and 5,000 colleges every year to find those recruits [4]. They canvas schools and current applicants for referrals. The names and contact information of the prospects are then used for follow-up contact. The Navy Recruiting Manual recommends the telephone as the best way to make the initial contact [5]. The manual also recommends mail-outs and social media networks as alternate ways to contact potential recruits. The goal of these contacts is to set up an appointment for an interview between the recruiter and the prospect.

Despite the widespread use of social media by other companies for targeted marketing and job placement, the U.S. Navy has not embraced its use beyond basic non-targeted marketing. The Navy Recruiting Manual only has one paragraph on using social media for recruiting purposes, and it focuses on how to document the contact; it does not discuss how to discover prospects [5]. This is further evidence that the U.S. military is focusing on social media as an additional advertising tool instead of as a recruiting tool.

Navy Recruiting Command lists its recruiting priorities as follows: Medical officers, Chaplains, SEALs, Navy Special Warfare, Navy Special Operations, Special Warfare Combatant-Craft Crewmen, Explosive Ordnance Disposal, Diver, Hospital Corpsmen, and Reserves [4]. All of these jobs require some kind of special qualifications or aptitudes. However, the methods that recruiters have now are insufficient to identify potential prospects with the right qualifications or aptitudes and the personality characteristics necessary to be a successful Sailor.

1.2 Research Questions

This research explores the use of social media, specifically Twitter, to determine if the personality of well-performing Navy personnel can be identified based on their Twitter use and if so, what other useful information can be determined that might differentiate a well-performing Navy Twitter user from a non-Navy Twitter user. The term "well-performing" is used to indicate those Sailors whose contribution to the Navy is positive; this research uses selection for promotion as a proxy for "well-performing."

By answering these questions, this research takes the first step in determining whether a tool to identify future recruits based on their Twitter activity would be both feasible and useful. This notional tool would allow recruiters to identify potential prospects with the right aptitude who would not otherwise consider a career in the Navy, and target them for recruitment.

1.3 Organization of Thesis

Chapter 2 provides background information on the study and characterization of personality traits, the Twitter social media platform, graph databases, the Linguistic Inquiry and Word Count (LIWC) software, and related research in this area. Chapter 3 covers the methodology

used to identify the accounts of Navy personnel and the equations used to identify each user's personality characteristics. Chapter 4 contains the findings of the research. Chapter 5 explains the model used to store the data and identifies some of the questions that can be answered by querying the data. Chapter 6 contains the conclusions and recommendations for future work on this topic.

THIS PAGE INTENTIONALLY LEFT BLANK

CHAPTER 2:
Background

This chapter provides background information on the different topics addressed in this thesis, including the Five Factor Model of personality, the Twitter social media platform, graph databases, and the Linguistic Inquiry and Word Count (LIWC) software.

2.1 Personality Traits

The field of psychology has been attempting to quantify humans via personality for at least the last century [6]. Many models have been proposed over the years, but few have withstood additional testing. However, the Five Factor Model of personality traits, also known as the Big Five, has been shown to be robust against different methods of testing and is the most commonly used approach for personality identification in psychology today. The personality traits identified in this thesis are based on the Five Factor Model.

2.1.1 The Five Factor Model

The central idea of the Five Factor Model is that all personality traits can be categorized into one of the five factors, and any person can be described by their rating for each of the factors [7]. The five factors are Agreeableness, Conscientiousness, Extroversion, Neuroticism, and Openness to Experience [8].

One weakness in the Five Factor Model is that there is no official definition of the terms; however, similar words are used to describe each of the factors across much of the research [9].

The five factors are:

- **Agreeableness**, described with terms such as trust, straightforwardness, altruism, compliance, modesty, and tender-mindedness
- **Conscientiousness**, described with terms such as competence, order, dutifulness, achievement striving, self-discipline, and deliberation

- **Extroversion**, described with terms such as warmth, gregariousness, assertiveness, activity, excitement-seeking, and positive emotions
- **Neuroticism**, described with terms such as anxiety, anger, depression, self-consciousness, impulsiveness, and vulnerability
- **Openness to Experience**, described with terms such as fantasy, aesthetics, feelings, actions, ideas, and culture [9]

There is no standard scale used to describe these factors; this research uses the same 0–1 scale as seen in [10].

2.2 Twitter

Twitter is a social media platform designed for microblogging; all posts are limited to 140 characters. Twitter provides a medium for users to post about their lives, activities, and opinions. Users are referenced by both a unique *screen name* chosen by the user and a unique user identification number assigned by Twitter. Although a user can change their screen name, their user identification number remains the same. Screen names are displayed on the pages through the Twitter site, and their identification numbers are available in the HTML code for a page. Users have the option to set their accounts to *protected*, which limits public access to any of their activity beyond basic profile data; without this restriction, all posts are available to the public.

Twitter posts are known as *tweets* or *statuses* and are also assigned unique identification numbers. People who are subscribed to a user's posts are known as *followers*. Users can *favorite* or *retweet* a post to indicate their support of that tweet. Within a tweet, a user can use a word or phrase (without spaces), called a *hashtag* and identified by the character #, which links that post to any other tweet containing the same hashtag. Twitter displays the most commonly used hashtags on its main page to show what is trending at any time. Users can embed photos or videos in their tweets. Other users can be referenced in a tweet by using the character @ and a screen name; these references are either a *reply*, where the tweet is a direct response to another tweet, or a *mention*. User mentions are more commonly used by users who are trying to get the attention of a celebrity. Although anyone can create an account using any name, celebrity accounts are *verified* by Twitter as actually belonging to the celebrity they are claiming to represent. An example of a tweet can be seen in Figure 1.

Figure 1: Example of a Tweet

2.2.1 Twitter API

Twitter is accessible for developers using an application programming interface (API). The Twitter API is divided into three categories: the REST API, the Streaming API, and the Streaming Firehose [11]. The REST API provides access to the Twitter data stream for individual transactions such as posting a tweet, reading a user profile or identifying followers. The Streaming API and the Streaming Firehose are both used for persistent connection transactions such as reading tweets over a period of time; the difference is in the

amount of the overall Twitter traffic that can be accessed [11]. This work exclusively used the REST API.

The API provides data in four different object types—*Tweets*, *Users*, *Entities*, and *Places*—using JavaScript Object Notation (JSON) strings. An example of a tweet in a formatted JSON string is shown in Figure 2. The types and formatting of information provided by Twitter in the JSON string is not the same for every object, even within the same object type; generally, if a field is empty or null, it is not returned as part of the JSON string at all. Twitter programmers also change the included metadata and formatting as they see fit and warn that developers' applications need to be able to tolerate the changes [11].

Tweet Object

A Tweet object provides both the text of the tweet and the metadata about the tweet. The fields that may be included in a Tweet object as of the time of data collection for this research are:

- *contributors*: A collection of users who contributed to the authorship of the tweet.
- *coordinates*: The latitude and longitude of the tweet.
- *created_at*: The date and time when the tweet was created.
- *favorite_count*: The number of users who have favorited this tweet.
- *id*: A unique integer identifier for the tweet.
- *in_reply_to_screen_name*: If the tweet is a reply to another tweet, this contains the screen name of the original author.
- *in_reply_to_status_id*: If the tweet is a reply to another tweet, this contains the ID number of the original tweet.
- *in_reply_to_user_id*: If the tweet is a reply to another tweet, this contains the ID number of the original author.
- *lang*: The language of the tweet text, if it can be determined.
- *place*: A Place object as described in Section 2.2.1.
- *retweeted_status*: If the tweet is a retweet, this field contains a Tweet object representing the original tweet.
- *source*: The application used to post the tweet.
- *text*: The actual text of the tweet.
- *user*: A User object, as described in Section 2.2.1, representing the user who posted

```
{
  "created_at": "Fri Jun 07 12:58:39 +0000 2013",
  "favorite_count": 1,
  "favorited": false,
  "hashtags": [
    "navy",
    "bestjobs"
  ],
  "id": 342988978418483201,
  "lang": "en",
  "media": [
    {
      "display_url": "pic.twitter.com/8kEbcFIbxN",
      "expanded_url": "http://twitter.com/jschreffler34/status/342988978418483201/photo/1",
      "id": 342988978422677504,
      "id_str": "342988978422677504",
      "indices": [
        60,
        82
      ],
      "media_url": http://pbs.twimg.com/media/BMKKqJzCAAA9n_o.jpg",
      "media_url_https":"https://pbs.twimg.com/media/BMKKqJzCAAA9n_o.jpg",
      "type": "photo",
      "url": "http://t.co/8kEbcFIbxN"
    }
  ],
  "retweeted": false,
  "source": "<a href=\"http://twitter.com/download/android\"rel=\"nofollow\">Twitter for Android</a>",
  "text": "Had some choppers on the flight line today #navy #bestjobs http://t.co/8kEbcFIbxN",
  "truncated": false,
  "user": {
    "created_at": "Wed May 29 21:54:47 +0000 2013",
    "default_profile": true,
    "description": "nun much to say went to high school at canon mac join the navy in 2012 traveled the world
      and made a lot of friends along the way",
    "favourites_count": 268,
    "followers_count": 51,
    "friends_count": 158,
    "id": 1468314306,
    "lang": "en",
    "location": "Virginia Beach, Virginia ",
    "name": "james schreffler",
    "profile_background_color": "C0DEED",
    "profile_background_image_url":"http://abs.twimg.com/images/themes/theme1/bg.png",
    "profile_background_tile": false,
    "profile_banner_url":"https://pbs.twimg.com/profile_banners/1468314306/1425740330",
    "profile_image_url":"https://pbs.twimg.com/profile_images/574222682062979072/47xTCQi-_normal.jpeg",
    "profile_link_color": "0084B4",
    "profile_sidebar_fill_color": "DDEEF6",
    "profile_text_color": "333333",
    "protected": false,
    "screen_name": "jschreffler34",
    "statuses_count": 36
  }
}
```


Figure 2: Example of the Tweet from Figure 1 as a formatted JSON string.

this tweet.

- *user_mentions*: A list of the users referenced in the Tweet, with shortened User objects for each user.

User Object

A User object provides the metadata about the user. The fields that may be included in a User object as of the time of data collection for this research are:

- *created_at*: The date and time that the user account was created.

- *description*: The user's free-text description of their account.
- *entities*: One or more Entity objects as described in Section 2.2.1.
- *favorites_count*: The number of tweets the user has favorited.
- *followers_count*: The number of followers the user has.
- *friends_count*: The number of accounts this user is following.
- *geo_enabled*: Indicates if the user has allowed geo-tagging of their tweets.
- *id*: A unique integer identifier of the user.
- *lang*: The default language for the user's interface.
- *location*: The user-defined location in a string format.
- *name*: The name of the user.
- *protected*: A Boolean variable that indicates if the user has protected their account. For a protected account, only the information in the User object JSON string is available; all other information, including tweets and followers, is only available to those that the user has explicitly granted permission to.
- *screen_name*: The screen name of the user.
- *status*: A Tweet object containing the user's most recent status.
- *statuses_count*: The number of tweets, including replies and retweets, that the user has posted.
- *url*: A URL provided by the user.

Entity Object

An Entity object provides additional metadata about a tweet or user. The fields that may be included in an Entity object as of the time of data collection for this research are:

- *hashtags*: A list of the hashtags contained in the object.
- *media*: A representation of the media elements in the object.
- *url*: A list of the URLs included in the object.
- *user_mentions*: A list of the users referenced in the Tweet, with shortened User objects for each user.

Place Object

A Place object provides additional metadata about a place. The place can be either the location where the tweeted was posted from or a place mentioned in the tweet. The fields

that may be included in a Place object as of the time of data collection for this research are:

- *bounding_box*: A set of coordinates that describe the bounds of the place.
- *country*: The country name of the place.
- *country_code*: A shortened form of the country name.
- *full_name*: The full name of the place in human-readable form.
- *id*: A unique string representing the place.
- *name*: A shortened form of the human-readable name.
- *place_type*: The type of place.

2.2.2 Access and Limitations

There are wrappers available for the Twitter API in many different programming languages in order to make it easier for developers to use the API. This work used Python and the wrapper `python-twitter` to access the API and for further data processing.

Access to the Twitter API requires a Twitter account and registration for a Twitter App Token, both of which are free and only require an email address in order to register. Access to the REST and Streaming APIs are also free; however, both have limitations on their use. The REST API is limited to 180 queries in a 15-minute window; this was a hindrance to data collection for this thesis as it greatly increased the time required to gather the necessary information. The Streaming API provides real-time access to tweets, but only a fraction of the total at any point—generally 1%, though it can be higher during low-traffic periods [12]. The only way to get access to 100% of tweets in real time is via the Twitter Firehose, which is a paid service.

2.3 Graph Databases

Relational database management systems (RDBMS) are the most common way that data is stored in a database. Data in an RDBMS is stored in relational tables and accessed via a Structured Query Language (SQL) [13]. Database management systems that do not use relational tables or SQL are collectively referred to as NoSQL databases. A graph database management system is one of several types of NoSQL databases, in which data is stored and queried using a graph model and graph theory, as opposed to the tables and cross-product queries of an RDBMS [13].

A graph is a set of vertices or nodes that are connected by edges. The edges may or may not be directional. Graph databases prioritize the relationships between data and allow complicated queries that follow through multiple connections, which are memory and processing-intensive in relational databases. Almost any data that can be modeled using an RDBMS can also be modeled in a graph database, but graph databases are especially useful for storing data such as business or social networks [13].

This work used the graph database program Neo4j and the query language Cypher to create and query the database. Neo4j uses *nodes*, *relationships*, *properties*, and *labels* as its basic building blocks. Nodes in Neo4j are equivalent to nodes or vertices in graphs. Relationships are equivalent to edges in graphs and are used to connect nodes. Both relationships and nodes can have properties, which add more detail to them. Labels are used to group nodes or relationships by type [13]. An example of a simple Neo4j graph is shown in Figure 3.

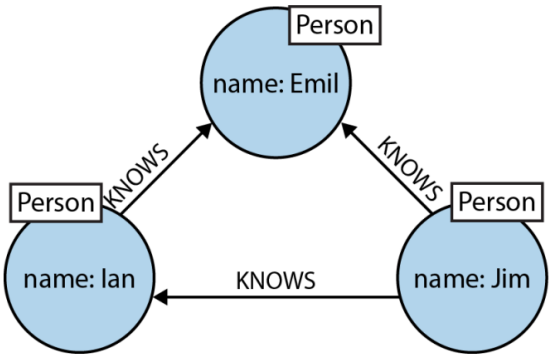


Figure 3: Simple graph pattern, where the blue circles are nodes with the label *Person* and the property *name*. The nodes are connected to each other with the relationship *KNOWS*.
Source:I. Robinson, J. Webber, and E. Eifrem, *Graph Databases: New Opportunities for Connected Data*, 2nd ed. Sebastopol, CA: O'Reilly Media, Inc, 2015.

Cypher is similar in format to SQL, the language used to query relational databases, but uses different reserve words. Figure 4 shows the key words available in Cypher. A simple question for the graph in Figure 3 would be to find out who the Person named `Jim` knows. The Cypher query for that question is:

```
MATCH (a:Person)-[:KNOWS]->(b:Person)
WHERE a.name = 'Jim'
RETURN b
```

which should return two nodes, a Person named `Ian` and a Person named `Emil`. Cypher can also be used to answer much more complicated questions.

`MATCH`	Identifies data matching the specified pattern
`RETURN`	Returns the data to the client
`WHERE`	Provides criteria for filtering pattern matching results.
`CREATE` and `CREATE UNIQUE`	Create nodes and relationships.
`MERGE`	Ensures that the supplied pattern exists in the graph, either by reusing existing nodes and relationships that match the supplied predicates, or by creating new nodes and relationships.
`DELETE`	Removes nodes, relationships, and properties.
`SET`	Sets property values.
`FOREACH`	Performs an updating action for each element in a list.
`UNION`	Merges results from two or more queries.
`WITH`	Chains subsequent query parts and forwards results from one to the next. Similar to piping commands in Unix.
`START`	Specifies one or more explicit starting points—nodes or relationships—in the graph.

Figure 4: Cypher Keywords and Descriptions.
Adapted from: I. Robinson, J. Webber, and E. Eifrem, *Graph Databases: New Opportunities for Connected Data*, 2nd ed. Sebastopol, CA: O'Reilly Media, Inc, 2015.

2.4 Linguistic Inquiry and Word Count

Linguistic Inquiry and Word Count (LIWC) is a software tool used to analyze text. Given a sample of text, LIWC counts the occurrences of different types of words as defined by a pre-loaded or user-defined dictionary of words and categorization of those words [14]. Table 1 shows a list of categories and example words that fall within those categories. The results for each category are returned as a percentage of the overall number of words in the sample. Words can fall into multiple categories or not be included in any category, so the sum of the percentages for the categories will not equal 100%. This work used LIWC2015 with the pre-loaded dictionary; no user-defined dictionaries were used.

2.5 Related Work

Many studies have been done to correlate personality and job performance. Although research prior to 1990 generally was unable to determine any correlation, more reliable

Category	Examples
Personal pronouns	I, them, her
Impersonal pronouns	it, it's, those
Articles	a, an, the
Prepositions	to, with, above
Auxiliary verbs	am, will, have
Common Adverbs	very, really
Conjunctions	and, but, whereas
Negations	no, not, never

Table 1: Example of LIWC words and categories.
Adapted from: J. Pennebaker, R. L. Boyd, K. Jordan, and K. Blackburn, "The development and psychometric properties of LIWC2015." The University of Texas at Austin, Austin, TX, 2015.

correlations have been determined since the general acceptance of the Five Factor Model and its use in these studies [6]. Conscientiousness has been consistently shown as the most important factor in overall job performance. The other factors' importance in job performance is based on the type of job [6].

In [15], researchers demonstrated that military personnel who showed low levels of depression and homesickness and who adjusted to the military lifestyle more easily also showed low levels of Neuroticism and higher levels of Extroversion and Openness to Experience. They also showed that those who were rated as effective by both their direct superior and by themselves showed higher levels of Conscientiousness than those not rated as effective. These studies show that identifying personality traits according to the Five Factor Model can provide useful information for identifying possible recruits.

In [16], researchers examined multiple models to automatically identify personality based on written input; that research was extended to include both essays and recorded snippets of conversations in [17]. In [18], researchers were able to predict user's personality in the Five Factor Model based on their Facebook activity. That work was extended to Twitter in [10]. In [19], users were classified by both personality and profession based on their Twitter activity. These papers show that it is possible to determine a person's personality traits based on their writing and social media activity. This research uses similar methodology, focusing specifically on Navy personnel, in order to determine if more useful information

can be determined based on their Twitter activity and personality.

The use of Navy promotion lists to identify Twitter accounts was previously done in [20]; this research uses the same methodology to identify accounts for further processing.

THIS PAGE INTENTIONALLY LEFT BLANK

CHAPTER 3:
Methodology

This chapter explains the methodology used to identify the accounts of Navy personnel, and the equations used to identify each user's personality characteristics.

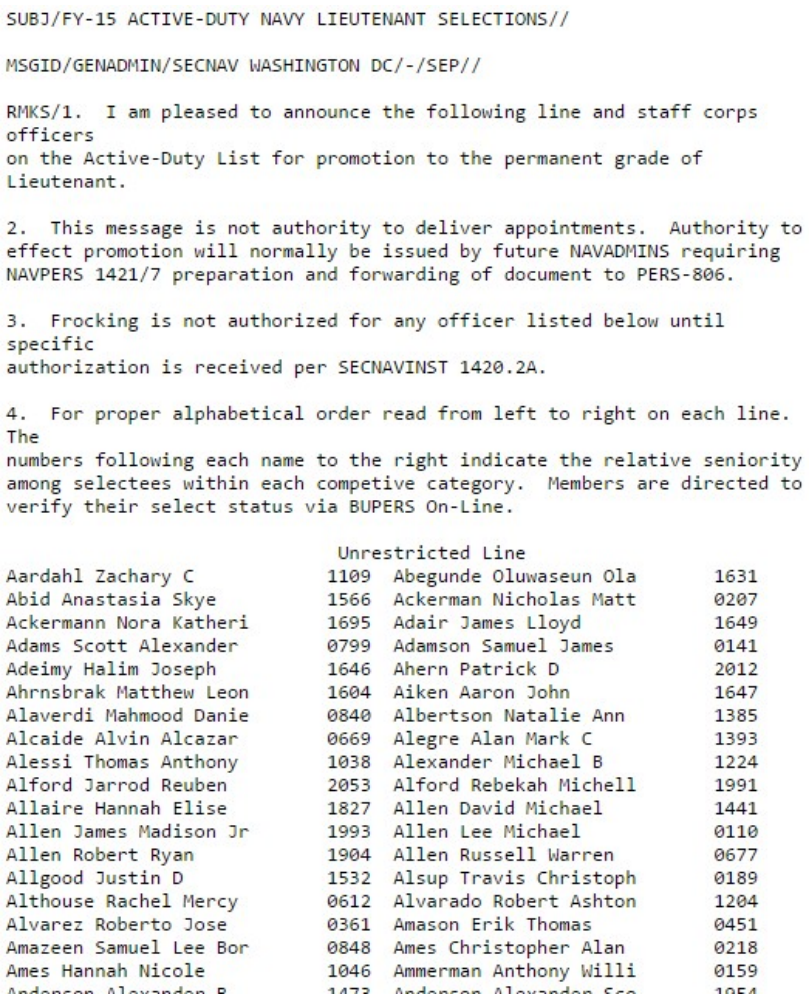
3.1 Identifying Navy Personnel

The data collection phase of this research began with identifying well-performing Navy personnel, defined as those who have been selected for a promotion to higher rank. All Navy promotion lists are published online and are publicly available; there are multiple different formats and sites with the data. Officer promotion lists are disseminated via record message traffic to all Navy units and posted to the Navy Bureau of Personnel (BUPERS) website in text format. Figure 5 shows the beginning of an officer promotion message. Enlisted promotion lists are generally posted in PDF format to the Navy All Hands page at `www.navy.mil` 24 hours after commands have been notified. Figure 6 shows an example of an enlisted promotion list.

Promotion lists are released twice a year for the pay grades E-4 through E-6 and once a year for pay grades E-7 through E-9 and O-3 through O-6. E-1 through E-3 and O-1 through O-2 promotions are based solely on time-in-grade and no lists of those promoted are published. O-7 and above promotions are based on assignments to a specific job and are announced as necessary throughout the year. This work used all of the promotion lists from Fiscal Year 2015, between October 2014 and September 2015, for the pay grades E-4 through E-8 and O-3 through O-5. There were a total of 54,580 names on all of these lists combined.

3.2 Identifying Twitter Accounts

After compiling the list of names, I used a python script and the `python-twitter` wrapper for the Twitter API to search for each of the names on Twitter. Each search request returned up to 100 user profile strings in JSON format, which were then converted to a comma-separated string and stored in a comma-separated values (CSV) file. Because of the large number of names that were searched for and the Twitter REST API query rate limits,



```
SUBJ/FY-15 ACTIVE-DUTY NAVY LIEUTENANT SELECTIONS//

MSGID/GENADMIN/SECNAV WASHINGTON DC/-/SEP//

RMKS/1.  I am pleased to announce the following line and staff corps
officers
on the Active-Duty List for promotion to the permanent grade of
Lieutenant.

2.  This message is not authority to deliver appointments.  Authority to
effect promotion will normally be issued by future NAVADMINS requiring
NAVPERS 1421/7 preparation and forwarding of document to PERS-806.

3.  Frocking is not authorized for any officer listed below until
specific
authorization is received per SECNAVINST 1420.2A.

4.  For proper alphabetical order read from left to right on each line.
The
numbers following each name to the right indicate the relative seniority
among selectees within each competive category.  Members are directed to
verify their select status via BUPERS On-Line.

                            Unrestricted Line
Aardahl Zachary C           1109  Abegunde Oluwaseun Ola       1631
Abid Anastasia Skye         1566  Ackerman Nicholas Matt       0207
Ackermann Nora Katheri      1695  Adair James Lloyd            1649
Adams Scott Alexander       0799  Adamson Samuel James         0141
Adeimy Halim Joseph         1646  Ahern Patrick D              2012
Ahrnsbrak Matthew Leon      1604  Aiken Aaron John             1647
Alaverdi Mahmood Danie      0840  Albertson Natalie Ann        1385
Alcaide Alvin Alcazar       0669  Alegre Alan Mark C           1393
Alessi Thomas Anthony       1038  Alexander Michael B          1224
Alford Jarrod Reuben        2053  Alford Rebekah Michell       1991
Allaire Hannah Elise        1827  Allen David Michael          1441
Allen James Madison Jr      1993  Allen Lee Michael            0110
Allen Robert Ryan           1904  Allen Russell Warren         0677
Allgood Justin D            1532  Alsup Travis Christoph       0189
Althouse Rachel Mercy       0612  Alvarado Robert Ashton       1204
Alvarez Roberto Jose        0361  Amason Erik Thomas           0451
Amazeen Samuel Lee Bor      0848  Ames Christopher Alan        0218
Ames Hannah Nicole          1046  Ammerman Anthony Willi       0159
Andersen Alexander R        1473  Andersen Alexander Sco       1954
```

Figure 5: An example of a record message for officer promotions.

this process took approximately 80 hours to complete and returned approximately 280,000 Twitter accounts.

Due to the nature of this research, it was important that only accounts actually belonging to Navy personnel were included in the data collection and analysis. Because of the large number of accounts, it was not feasible to look at each account individually to verify whether or not it actually belonged to a member of the Navy. Each user profile was instead run through a script that checked the JSON string for matches from a list of key words, including references to the Navy, Navy titles, and common Navy locations; the full list of key words is shown in Table 2. These terms were case-insensitive in the search. This returned 6,884

NAME,ERATE	BROWN KENNETH J,ABE2	COPELAND DIYON,ABE3	HAGWOOD BRITTAN,ABE3
TURRONE ROBERT,ABE1	MARTIN STEVEN E,ABE2	CREDLE CLIFFORD,ABE3	STGERMAIN NOELL,ABE3
HOLLENBAUGH JON,ABE1	OTERO MARIO MEN,ABE2	EVANS JAMESHA L,ABE3	PETTIS RODRICK,ABE3
ABOKI SOSSI SIK,ABE1	GEWECKE BRANDON,ABE2	DAVIS ANDREW MI,ABE3	RAMIREZ JOSE LU,ABE3
MARKOWSKI ANTHO,ABE1	FRADEL MICHAEL,ABE2	WITHROW MICHELL,ABE3	BARAHONA GUSTAV,ABE3
SHAW BENJAMIN R,ABE1	DEVRIES ANDY,ABE2	ALBRIGHT AMOS J,ABE3	PACHECOMENDEZ D,ABE3
PINTORE JOHN MA,ABE1	SPOONER CRAIG A,ABE2	HOPSON DEVENYIS,ABE3	ALLEN SPENCER R,ABE3
BOYER MATTHEW J,ABE1	KOHN BENJAMIN P,ABE3	BLUHM CORY LEE,ABE3	CARRILLO EDUARD,ABE3
SOLORIO LEWISAN,ABE1	MORRIS JAKE VIN,ABE3	MIKETINAS NIKOL,ABE3	MATHEWS GEOFFRE,ABE3
PAGLINGAYEN DEN,ABE1	BROOKS CHRISTIA,ABE3	ROUSSEAU DANIEL,ABE3	ARNOLD MARLA BE,ABE3
SMITH SAMANTHA,ABE1	DYCK GEORGE VER,ABE3	ALVARADO MASON,ABE3	ARROYO AMANDA L,ABE3
WILSON TONGHUI,ABE1	BROWN DANA ALAN,ABE3	TESTER JACOB LE,ABE3	FUETTE MARK STE,ABE3
RODA LEANDRO FR,ABE1	THYNE KATHERINE,ABE3	MONTAGUE KATHLE,ABE3	GAUSE CEDRICK D,ABE3
TAGIC DANIEL,ABE1	POUNALL CAMELIA,ABE3	FORTIN JUSTIN T,ABE3	BARAJAS RAQUEL,ABE3
BELL AMANDA MAR,ABE2	TOYLO EMERIEJOY,ABE3	HARRIS JOSHUA M,ABE3	MORALES DOMINIC,ABE3
MOORE GEORGE AL,ABE2	NGUESSAN SHANNO,ABE3	THOMPSON SEAN G,ABE3	BUTTARS DESIREE,ABE3
CLARO CARLOUIE,ABE2	DOWDELL MATTHEW,ABE3	GONZALEZ JOEL S,ABE3	ABERCROMBIE TYL,ABE3
GUMBS ANTHONY B,ABE2	MARTINEZ GABRIE,ABE3	PICKENS RUFUS J,ABE3	LAXAMANA KAMYLL,ABE3
ANIGILAJE OLUWA,ABE2	MAUE JESSICA AN,ABE3	SMITHMICKLES JE,ABE3	RINALDI ROBERT,ABE3
TILLIS RYAN ABR,ABE2	MANCINI DAMIANO,ABE3	JOHNSON TIARA M,ABE3	RODRIGUEZ CARLO,ABE3
LOUIS RION RICH,ABE2	ANDERSON TATIAN,ABE3	SILFIES ANGELA,ABE3	CASTRO JEREMIE,ABE3
DJUREN JACOBUS,ABE2	RIDALL JILLIAN,ABE3	WALKER WENDEL,ABE3	CRAIG KARRI KRI,ABE3
DERKOWSKI RUSTY,ABE2	RIGATTI FRANCES,ABE3	STEMLER LYANNE,ABE3	ROBERTS MARCUS,ABE3
JACKSON BRITTAN,ABE2	FATTY MUTARR,ABE3	EDWARDS SARA TE,ABE3	HERNANDEZ RENE,ABE3
LEHEW SCOTT JEF,ABE2	MORRIS TIERRA N,ABE3	CIZAUSKAS IZAAC,ABE3	ARNOLD VALESHA,ABE3
SMITH DEMETRIUS,ABE2	PRATT LUCAS PAT,ABE3	MORRIS BRANDON,ABE3	JONES CODY ALLE,ABE3
CODY JONATHAN L,ABE2	DOWNES MICHAEL,ABE3	SALAZAR NICOLE,ABE3	HILL ZACHARY TA,ABE3
FINAN JENNIFER,ABE2	MENDOZA LESTER,ABE3	THOMPSON PATRIC,ABE3	RYDER ARTIOM J,ABE3
BERNA SEAN ROBE,ABE2	PERRY NICOLE DE,ABE3	HARRIS COLTON T,ABE3	ARIZAGA ADAM,ABE3
HEDIGER ZACHARY,ABE2	DIECKMAN JEROME,ABE3	PRATHER DOUG WA,ABE3	BACON LEONARD L,ABE3
WOLFE KATLIN AN,ABE2	SMITH KEISHA MA,ABE3	BENTLEY WESTON,ABE3	TOONE MICHAEL W,ABE3
ROMAN MONICA,ABE2	AYERS SHELBY RE,ABE3	JOHNSON LANEICE,ABE3	DENNIS TASANIA,ABE3
LANIER CARL VIN,ABE2	POLYAK JOSHUA K,ABE3	DAVIS DEMAREO D,ABE3	ROMEROLOPEZ KEN,ABE3
MARTINI GLEN MI,ABE2	ARMSTRONG WIL A,ABE3	MAKOVEC AIMEE L,ABE3	ADJOGAH KOSSI I,ABF1
DRAHOS JACOB E,ABE2	SNOWDEN JASPER,ABE3	GIBBS ANTHONY P,ABE3	CLAUTICE JEREMY,ABF1
ENGLAND HOLLY N,ABE2	ALT DANIEL RAYM,ABE3	CANTRALL TYLER,ABE3	RHODES NATHAN I,ABF1
HERRIG BRIAN SC,ABE2	WOLFE STEFAN TY,ABE3	MORGAN AUSTIN C,ABE3	HODGE JOSEPH RO,ABF1
PORTER KYLE AND,ABE2	CARO JESSICA NI,ABE3	HOLIFIELD MANDR,ABE3	ANDERSON QUENTI,ABF1
LEE ERIC NEWTON,ABE2	MELVIN BRANDON,ABE3	CAPRA ZACHARY M,ABE3	BURNS DERRICK A,ABF1
LARSON ANDREW D,ABE2	BOYER KATELYN P,ABE3	APLEY KAITLIN M,ABE3	MARTIN ROBERT E,ABF1
HERNANDEZ JOHNM,ABE2	WALKER SHARITA,ABE3	JACKSON KENNON,ABE3	BALAJADIA DANIE,ABF1
LOCKHART BERNAD,ABE2	COMBS AARON RAH,ABE3	HAMPSHIRE CLARE,ABE3	BROWNEHOLLIER A,ABF1

Figure 6: An example of a promotion list on the Navy All Hands' page.

possible matches.

Each of the remaining user profile CSV strings was prepended with an **m**—to signify maybe—and then examined manually in an Excel spreadsheet. Accounts that belonged to users who were obviously in the Navy were marked with a **y** and accounts that belonged to users who were obviously not in the Navy were marked with an **n**. Obvious disqualifiers included: having a foreign location that was not one of the known overseas military locations; profile name not matching the requested search name; and profile descriptions mentioning an occupation that was not the U.S. Navy. Protected accounts were also excluded, whether or not the user could be identified as being in the Navy, because the protected status prevents access to their tweets, which is what this research was looking for.

This step of the process identified 380 accounts that obviously belonged to Navy personnel, 5,839 accounts that obviously did not belong to Navy personnel, and 665 accounts that could not be categorized either way. These 665 accounts were then examined manually

Navy	USN	naval
sea	sub	pilot
aviat	Sailor	USS
petty	chief	SWO
military	Newport	Groton
Washington	Annapolis	Norfolk
Virginia Beach	Va Beach	Charleston
King's	Jacksonville	Mayport
Pensacola	Millington	Corpus
Great Lakes	San Diego	Monterey
Everett	Bremerton	Bangor
Pearl H	Yoko	Sasebo
	Rota	

Table 2: List of search terms used to identify Navy Twitter accounts

by opening their Twitter page and searching their pictures, tweets, and who they were following to determine if they were actually Navy personnel. As seen in [20], many of the Navy accounts could be easily identified by profile pictures of the user in uniform or tweets about Navy activities. Examining who a user was following generally did not provide any useful data; following one or more of the official Navy accounts was not a enough in itself to declare the account as belonging to a Navy member, though it was combined with other individually inconclusive factors. When there was any doubt about whether the user was in the Navy, I erred on the side of caution and excluded them. The final number of verified Navy personnel user accounts was 500.

3.2.1 Collecting Tweets

For each of the 500 verified Navy accounts, I queried the Twitter REST API for the most recent 2000 tweets, including retweets of others' tweets; for those users with fewer than 2000 tweets, their full tweet history was returned. The earliest tweet came from 7 June 2008, and the longest time between a user's most recent tweet and their first or 2000th tweet—whichever was later—was seven years and two months. There were a total of 72,678 tweets, with an average of 145 tweets per user and a median of 184 tweets per user.

3.3 Identifying Personality Characteristics of Each User

Once the data was collected and stored in the database, it was analyzed using LIWC2015 as described in Section 2.4. Each user's tweets were analyzed together as an overall corpus.

To determine a user's level for each of the five personality factors, I used the basic linear regression equation

$$Y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \ldots \beta_m x_{im} + \epsilon_i, \tag{3.1}$$

where Y_i represents the ith user's level of a certain character trait Y, x_{ij} is the value of the jth independent variable for user i as determined by LIWC, and β_j is the coefficient of the jth independent variable, as calculated using Equation 3.3.

Each of the five character traits uses a different set of independent variables, based on the work by Golbeck et al. in [10], which determined the correlation coefficient between a user's level of a certain trait and the results of using LIWC on their Twitter corpus. These correlation coefficient are shown in Figure 7.

For Extroversion, the LIWC categories that showed significant correlation were: Social Processes, Family, Health, Question Marks and Parentheses. For Agreeableness, the LIWC categories that showed significant correlation were: You, Causation, Ingestion, Achievement, and Money. For Conscientiousness, the LIWC categories that showed significant correlation were: You, Auxiliary Verbs, Future Tense, Negations, Negative Emotions, Sadness, Cognitive Mechanisms, Discrepancy, Feeling, Work, Death, Fillers, Commas, Colons and Exclamation Marks. For Neuroticism, the LIWC categories that showed significant correlation were: Hearing, Feeling, Religion and Exclamation Marks. For Openness to Experience, the LIWC categories that showed significant correlation were: Articles, Quantifiers, Causation, Certainty, Biological Processes, Body, Work, Exclamation Marks, and Parentheses.

For each character trait, a matrix was constructed in which each row represented a single user, the first column consisted of 1's to represent the lack of x value for β_0 and each subsequent column represented one of the significant LIWC categories for that character trait. For example, if User 1 has a score of 1.37 for You, 0.8 for Causation, 0.31 for Ingestion, 1.68 for Achievement and 0.44 for Money and User 2 has a score of 6.27 for You, 0.85 for

Causation, 0.78 for Ingestion, 1.56 for Achievement and 0.17 for Money, then the first lines of the matrix for Agreeableness would be:

$$\begin{bmatrix} 1 & 1.37 & 0.8 & 0.31 & 1.68 & 0.44 \\ 1 & 6.27 & 0.85 & 0.78 & 1.56 & 0.17 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix}.$$

The matrix for Agreeableness will hereafter be referred to as $\hat{X}_A$.

The vector of β values for Agreeableness can be written as $\hat{\beta}_A$ and the vector of Y values for Agreeableness can be written as $\hat{Y}_A$, leading to the equation

$$\hat{Y} = \hat{\beta}_A \hat{X}_A + \epsilon. \tag{3.2}$$

$\hat{X}_A$ consists of known values as computed by LIWC. $\hat{Y}_A$ represents the values I am trying to calculate. $\hat{\beta}_A$ can be calculated using the formula for ordinary least squares estimation,

$$\hat{\beta}_A = (\hat{X}_A^T \hat{X}_A)^{-1} \hat{X}_A^T \hat{Y}_A, \tag{3.3}$$

where T indicates the transpose matrix and -1 indicates the inverse matrix. $(\hat{X}_A^T \hat{X}_A)^{-1}$ can be calculated from the known values, but $\hat{Y}_A$ is unknown and therefore must be estimated from the expected value and standard deviation of Agreeableness, hereafter referred to as Y_A, as well as the expected value, standard deviation, and correlation for each x_j. The expected value and standard deviation of Y_A and the correlation between Y_A and x_j are taken from [10], as seen in Figures 7 and 8.

Because that work did not include the expected value or the standard deviation for each x_j, those values are computed using the data in this research. This is possible due to the assumption that the two data sets represent a sufficiently similar population.

The second half of Equation 3.3, $\hat{X}_A^T \hat{Y}_A$, can be written as

$$\hat{X}_A^T \hat{Y}_A = \begin{bmatrix} n\bar{Y}_A \\ \sum_{i=1}^{n} x_{i1} Y_{Ai} \\ \sum_{i=1}^{n} x_{i2} Y_{Ai} \\ \vdots \\ \sum_{i=1}^{n} x_{im} Y_{Ai} \end{bmatrix}.$$

Using the Pearson product-moment correlation coefficient,

$$\sum_{i=1}^{n} x_{ij} Y_{Ai} = \rho(y, x_j)(n-1) SD_{Y_A} SD_{x_j} + n\bar{Y}_A \bar{x}_j;$$

therefore

$$\hat{X}_A^T \hat{Y}_A = \begin{bmatrix} n\bar{Y}_A \\ \rho(y, x_1)(n-1) SD_{Y_A} SD_{x_1} + n\bar{Y}_A \bar{x}_1 \\ \rho(y, x_2)(n-1) SD_{Y_A} SD_{x_2} + n\bar{Y}_A \bar{x}_2 \\ \vdots \\ \rho(y, x_m)(n-1) SD_{Y_A} SD_{x_m} + n\bar{Y}_A \bar{x}_m \end{bmatrix}.$$

Using n=500—the number of user accounts in the data set—and substituting the known values for Agreeableness gives

$$\hat{X}_A^T \hat{Y}_A = \begin{bmatrix} (500)(0.697) \\ (0.364)(499)(0.162)(1.855) + (500)(0.697)(2.295) \\ (-0.258)(499)(0.162)(1.298) + (500)(0.697)(1.1148) \\ (0.247)(499)(0.162)(0.937) + (500)(0.697)(0.64174) \\ (-0.240)(499)(0.162)(1.172) + (500)(0.697)(1.377) \\ (-0.259)(499)(0.162)(0.782) + (500)(0.697)(0.4996) \end{bmatrix} = \begin{bmatrix} 348.5 \\ 854.25 \\ 360.27 \\ 242.35 \\ 457.18 \\ 157.75 \end{bmatrix}.$$

Calculating out Equation 3.3 gives

$$\hat{\beta}_A = \begin{bmatrix} 0.702 \\ 0.0262 \\ -0.0260 \\ 0.0331 \\ -0.0250 \\ -0.0455 \end{bmatrix},$$

and Equation 3.1 for Agreeableness can be rewritten as

$$\begin{aligned} Y_{Ai} &= 0.702 + (0.262)x_{i_{You}} + (-0.0260)x_{i_{Causation}} + (0.0331)x_{i_{Ingestion}} \\ &\quad + (-0.0250)x_{i_{Achievement}} + (-0.0455)x_{i_{Money}} + \epsilon_i, \end{aligned}$$

which can then be applied to each user, resulting in an Agreeableness value for that user. Using the same equations and steps for the other four factors produces the equations:

$$\begin{aligned} Y_{Ni} &= 0.224 + (0.0720)x_{i_{Hearing}} + (0.0908)x_{i_{Feeling}} \\ &\quad + (0.157)x_{i_{Religion}} + (0.0192)x_{i_{ExclamationMarks}} + \epsilon_i, \end{aligned}$$

$$\begin{aligned} Y_{Ci} &= 0.634 + (0.0378)x_{i_{You}} + (-0.00136)x_{i_{AuxVerbs}} + (-0.0323)x_{i_{Future}} \\ &\quad + (-0.0308)x_{i_{Negations}} + (0.0225)x_{i_{NegEmotions}} + (-0.0961)x_{i_{Sadness}} \\ &\quad + (0.0104)x_{i_{CogMechanisms}} + (-0.0909)x_{i_{Discrepancy}} + (-0.0241)x_{i_{Feeling}} \\ &\quad + (0.0242)x_{i_{Work}} + (-0.187)x_{i_{Death}} + (-0.268)x_{i_{Fillers}} \\ &\quad + (-0.227)x_{i_{Commas}} + (0.104)x_{i_{Colons}} + (0.0148)x_{i_{ExclamationMarks}} + \epsilon_i, \end{aligned}$$

$$
\begin{aligned}
Y_{Oi} &= 0.583 + (0.0208)x_{i_{Articles}} + (0.0153)x_{i_{Quantifiers}} + (0.0294)x_{i_{Causation}} \\
&\quad + (0.0373)x_{i_{Certainty}} + (0.00110)x_{i_{BioProcesses}} + (-0.0150)x_{i_{Body}} \\
&\quad + (0.0249)x_{i_{Work}} + (-0.00865)x_{i_{ExclamationMarks}} + (-0.0436)x_{i_{Parentheses}} + \epsilon_i,
\end{aligned}
$$

and

$$
\begin{aligned}
Y_{Ei} &= 0.481 + (0.00999)x_{i_{SocialProcesses}} + (0.141)x_{i_{Family}} + (-0.0861)x_{i_{Health}} \\
&\quad + (0.0321)x_{i_{QuestionMarks}} + (-0.0531)x_{i_{ParenthesesMarks}} + \epsilon_i.
\end{aligned}
$$

By applying these five equations to the LIWC results, the level of each personality factor can be calculated for each user.

3.3.1 Other Statistical Analyses

For each user, statistics were also collected for items not measured by LIWC. These non-language data points are:

- **Followers**: the number of other accounts that are following a user.
- **Following**: the number of other accounts that a user is following.
- **Favorites**: the number of tweets that the user has marked as a favorite.
- **Tweets**: the number of tweets that a user has posted that are included in this data set as described in Section 3.2.
- **Retweets**: the number of a user's tweets that were a retweet of another user's post.
- **Replies**: the number of a user's tweets that were a reply to another user's post.
- **Hashtags**: the total number of hashtags that a user has posted.
- **Media**: the total number of photos and videos that a user has posted.
- **Words per tweet**: the total number of words of a user normalized by the number of tweets the user has posted.
- **Retweets per tweet**: the number of a user's retweets normalized by the number of tweets the user has posted.
- **Replies per tweet**: the number of a user's replies normalized by the number of tweets

the user has posted.

- **Hashtags per tweet**: the number of hashtags a user has included normalized by the number of tweets the user has posted.
- **Media per tweet**: the number of photos and videos that a user has included normalized by the number of tweets the user has posted.
- **Followers/Following**: the ratio between the number of followers a user has and the number of accounts a user is following.

Language Feature	Examples	Extro.	Agree.	Consc.	Neuro.	Open.
"You"	(you, your, thou)	0.068	**0.364**	**0.252**	-0.212	-0.020
Articles	(a, an, the)	-0.039	-0.139	-0.071	-0.154	**0.396**
Auxiliary Verbs	(am, will, have)	0.033	0.042	**-0.284**	0.017	0.045
Future Tense	(will, gonna)	0.227	-0.100	**-0.286**	0.118	0.142
Negations	(no, not, never)	-0.020	0.048	**-0.374**	0.081	0.040
Quantifiers	(few, many, much)	-0.002	-0.057	-0.089	-0.051	**0.238**
Social Processes	(mate, talk, they, child)	**0.262**	0.156	0.168	-0.141	0.084
Family	(daughter, husband, aunt)	**0.338**	0.020	-0.126	0.096	0.215
Humans	(adult, baby, boy)	0.204	-0.011	0.055	-0.113	**0.251**
Negative Emotions	(hurt, ugly, nasty)	0.054	-0.111	**-0.268**	0.120	0.010
Sadness	(crying, grief, sad)	0.154	-0.203	**-0.253**	0.230	-0.111
Cognitive Mechanisms	(cause, know, ought)	-0.008	-0.089	**-0.244**	0.025	0.140
Causation	(because, effect, hence)	0.224	**-0.258**	-0.155	-0.004	**0.264**
Discrepancy	(should, would, could)	0.227	-0.055	**-0.292**	0.187	0.103
Certainty	(always, never)	0.112	-0.117	-0.069	-0.074	**0.347**
Perceptual Processes						
Hearing	(listen, hearing)	0.042	-0.041	0.014	**0.335**	-0.084
Feeling	(feels, touch)	0.097	-0.127	**-0.236**	**0.244**	0.005
Biological Processes	(eat, blood, pain)	-0.066	0.206	0.005	0.057	**-0.239**
Body	(cheek, hands, spit)	0.031	0.083	-0.079	0.122	**-0.299**
Health	(clinic, flu, pill)	**-0.277**	0.164	0.059	-0.012	-0.004
Ingestion	(dish, eat, pizza)	-0.105	**0.247**	0.013	-0.058	-0.202
Work	(job, majors, xerox)	0.231	-0.096	**0.330**	-0.125	**0.426**
Achievement	(earn, hero, win)	-0.005	**-0.240**	-0.198	-0.070	0.008
Money	(audit, cash, owe)	-0.063	**-0.259**	0.099	-0.074	0.222
Religion	(altar, church, mosque)	-0.152	-0.151	-0.025	**0.383**	-0.073
Death	(bury, coffin, kill)	-0.001	0.064	**-0.332**	-0.054	0.120
Fillers	(blah, imean, youknow)	0.099	-0.186	**-0.272**	0.080	0.120
Punctuation						
Commas		0.148	0.080	**-0.24**	0.155	0.170
Colons		-0.216	-0.153	**0.322**	-0.015	-0.142
Question Marks		**0.263**	-0.050	0.024	0.153	-0.114
Exclamation Marks		-0.021	-0.025	**0.260**	**0.317**	**-0.295**
Parentheses		**-0.254**	-0.048	-0.084	0.133	**-0.302**
Non-LIWC Features						
GI Sentiment		0.177	-0.130	-0.084	-0.197	**0.268**
Number of Hashtags		0.066	-0.044	-0.030	-0.217	**-0.268**
Words per tweet		**0.285**	-0.065	-0.144	0.031	0.200
Links per tweet		-0.061	-0.081	**0.256**	-0.054	0.064

Figure 7: Pearson correlation values between feature scores and personality scores. Significant correlations are shown in bold for $p < 0.05$. Only features that correlate significantly with at least one personality trait are shown.

Source: J. Golbeck, C. Robles, M. Edmondson, and K. Turner, "Predicting personality from Twitter," in *Privacy, Security, Risk and Trust (PASSAT) and 2011 IEEE Third International Conference on Social Computing (SocialCom)*, University of Maryland, College Park. IEEE, 9-11 Oct 2011 2011, pp. 149–149–156. [Online]. Available: http://ieeexplore.ieee.org/xpls/icp.jsp?arnumber=6113107.

	Agree.	Consc.	Extra.	Neuro.	Open.
Average	0.697	0.617	0.586	0.428	0.755
Stdev	0.162	0.176	0.190	0.224	0.147

Figure 8: Expected values and standard deviation of personality characteristics, normalized on a 0–1 scale.
Source: J. Golbeck, C. Robles, M. Edmondson, and K. Turner, "Predicting personality from Twitter," in *Privacy, Security, Risk and Trust (PASSAT) and 2011 IEEE Third International Conference on Social Computing (SocialCom)*, University of Maryland, College Park. IEEE, 9-11 Oct 2011 2011, pp. 149–149–156. [Online]. Available: http://ieeexplore.ieee.org/xpls/icp.jsp?arnumber=6113107.

CHAPTER 4:
Analysis

This chapter presents the results of the research. Analysis of those results shows that the mean value of each character trait matched those from the random selection of Twitter users in the study by Golbeck et al. [10]. The high level conclusion is that, while the personality traits of Navy Twitter users can be determined based on their Twitter activity, that information is insufficient as the sole predictor of who will be a good fit for Navy service.

4.1 Results

Using the formulas as described in Section 3.3, every user's level of each of the five personality traits was calculated. Figure 9 shows a boxplot for each of the character traits, with the colored area representing the values between the first and third quartiles, the outer horizontal lines representing the minimum and maximum values, the horizontal line in the colored area indicating the median value, and the small circles representing the outliers, except those discussed in Subsection 4.2.

The formula used to calculate each user's character traits based on their LIWC textual analysis and the means and correlations from [10] resulted in the mean of the sample of Navy users matching the mean of the sample from [10]. As a result, comparing the means of the Navy population to the wider Twitter population is not possible. However, some other useful information can be derived from other statistics.

4.1.1 Character Trait Distributions

Although the mean value of each character trait matched that given in Golbeck et al., the standard deviations of the traits of the Navy users were generally lower than those given in that work [10]. The standard deviations of each of the traits in the Five Factor Model from Golbeck et al., and this work are displayed in Table 3.

Conscientiousness was the only trait that had essentially the same standard deviation between the earlier work and this research; the other four traits had significantly lower standard

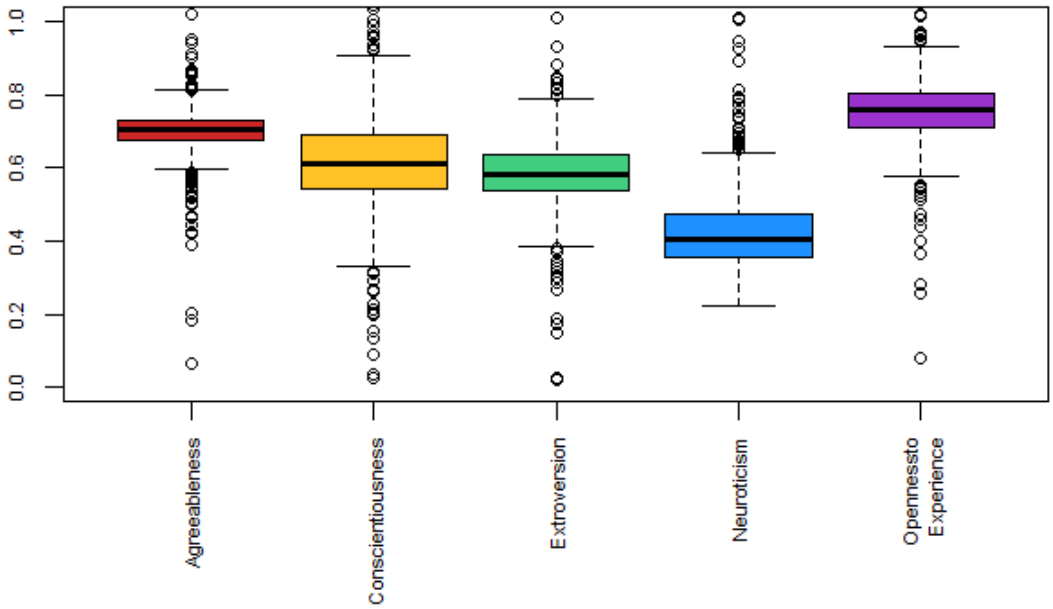


Figure 9: Boxplot showing the results of each of the Five Factors, with outliers trimmed.

	Agree.	Consc.	Extro.	Neuro.	Open.
Sample Population	0.162	0.176	0.190	0.224	0.147
Navy Population	0.090	0.178	0.115	0.144	0.123

Table 3: Standard deviation of character traits for Navy personnel and earlier research.
Adapted from: J. Golbeck, C. Robles, M. Edmondson, and K. Turner, "Predicting personality from twitter," in *Privacy, Security, Risk and Trust (PASSAT) and 2011 IEEE Third International Conference on Social Computing (SocialCom)*, University of Maryland, College Park. IEEE, 9-11 O ct 2011 2011, pp. 149–149–156. [Online]. Available: http://ieeexplore.ieee.org/xpls/icp.jsp?arnumber=6113107.

deviations. This shows that the Navy population has a more homogeneous personality makeup than the random selection of Twitter users from Golbeck et al.

As expected in a population, each trait displays a normal distribution. The Agreeableness values, as shown in Figure 10, have a narrow, sharp peak at the average, reflecting the low standard deviation seen in Table 3. This indicates that most of the Navy Twitter users had about average levels of Agreeableness. Conscientiousness, which had the highest standard deviation of the traits, exhibits a smoother curve with heavier tails at either end, as shown in

Figure 11. This finding was surprising because the work by Cooper and Pervin [6] showed that Conscientiousness is the trait most closely linked to job performance, and the sample population is of well-performing Navy personnel.

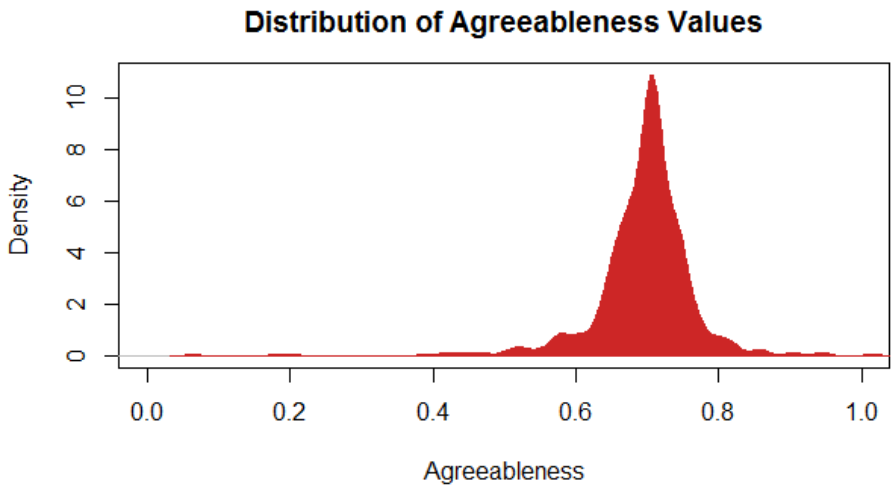


Figure 10: Density graph of Agreeableness values.

The distribution of Extroversion values is wider than that of Agreeableness, but narrower than Conscientiousness, with small peaks in the low end of the tail, indicating that, although the majority of the sample of Navy personnel have about average levels of Extroversion, there are a significant number that have very low to low Extroversion. As shown by DeJong et al. [15], people with higher levels of Extroversion adjust more easily to the military lifestyle; this work shows that those with lower levels of Extroversion can still perform well in a military lifestyle.

The density graph of Neuroticism values, as shown in Figure 13, displays a significant side peak below the overall average. This is consistent with the findings of DeJong et al. [15] that lower levels of Neuroticism correlate with ease of adjustment to the military lifestyle. The density graph of Openness to Experience, Figure 14, displays similar characteristics as the Extroversion graph but with a small rise above the average, very near the maximum possible value of 1. These users with very high levels of Openness to Experience are again consistent with DeJong et al. [15].

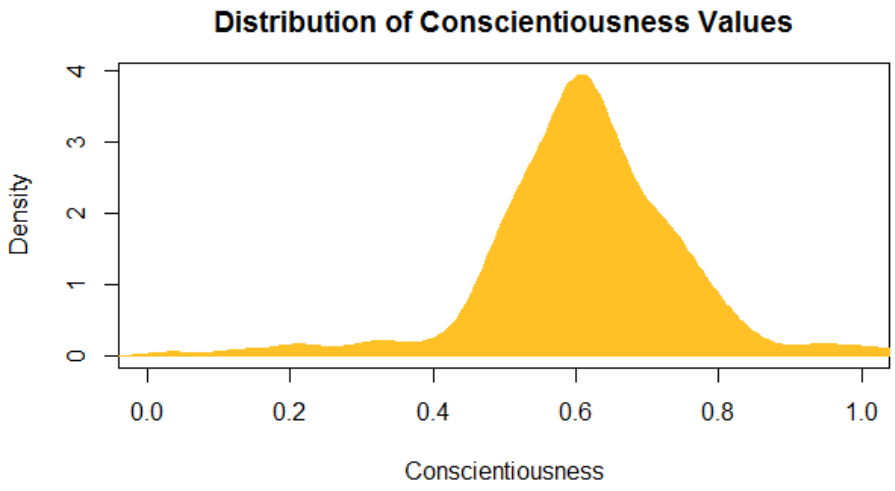


Figure 11: Density graph of Conscientiousness values.

4.1.2 Non-language Correlations

Correlations between each trait and the non-language data points as defined in Section 3.3.1 were calculated; the full results are displayed in Table 4. The shaded cells indicate those correlation coefficients which were significantly different from 0, where $p < 0.05$. There was no strong correlation seen between any of the non-language data and a user's level of each of the character traits; replies per tweet had a moderate correlation with both Agreeableness and Extroversion.

4.2 Calculation Anomalies

Although the measure of each trait should be between zero and one, each of the traits had a few users whose results were outside of that bounding, with values either below zero or above one. These errors occurred due to a disproportionately high value for one or more of the LIWC categories used to calculate the trait value. These users generally had a very small input size; of the 30 users who had at least one trait outside of the expected range, 25 had fewer than 200 words in their Twitter sample. These values outside of the expected range were included in all statistical calculations but are not displayed on any of the plots in this chapter.

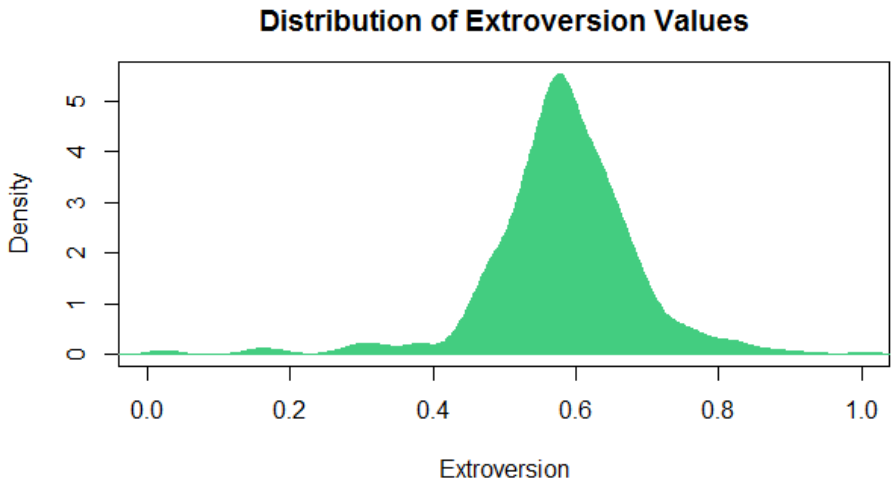


Figure 12: Density graph of Extroversion values.

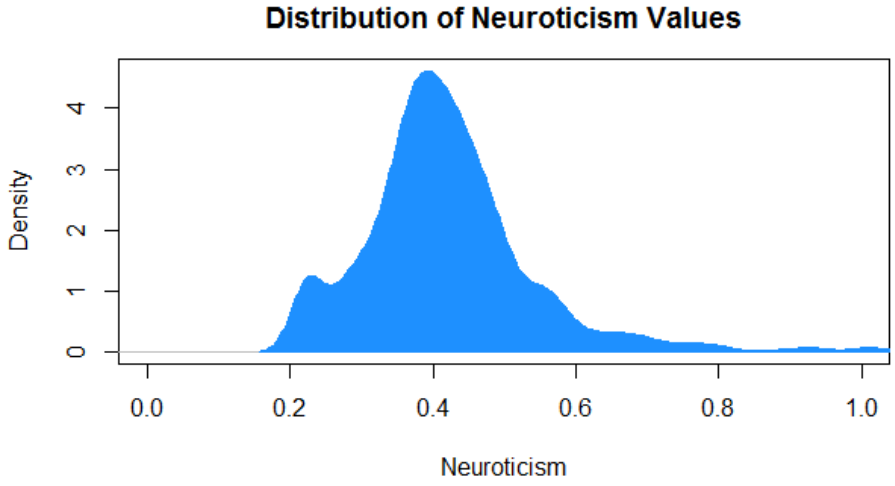


Figure 13: Density graph of Neuroticism values.

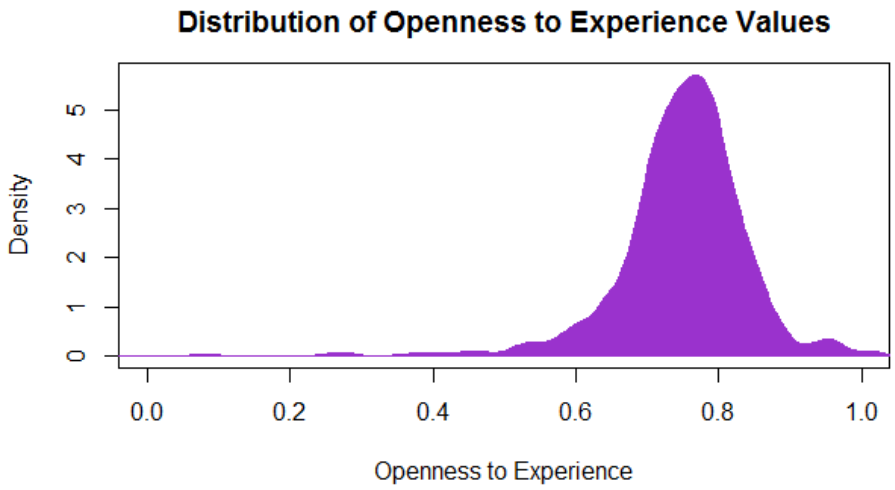


Figure 14: Density graph of Openness to Experience values.

	Agree.	**Consc.**	**Extro.**	**Neuro.**	**Open.**
Followers	-0.033	0.042	0.017	0.021	-0.001
Following	-0.009	0.016	-0.057	0.022	-0.050
Favorites	0.004	-0.010	-0.005	-0.038	0.007
Tweets	0.108	-0.012	0.016	-0.018	-0.086
Retweets	0.051	-0.021	0.005	-0.043	-0.006
Replies	0.115	0.002	0.110	-0.032	-0.031
Hashtags	0.007	0.032	-0.037	-0.032	-0.071
Media	0.042	-0.031	-0.096	-0.061	-0.107
Words per tweet	0.009	0.126	-0.015	-0.075	-0.067
Retweets per tweet	0.053	-0.021	-0.013	-0.034	-0.001
Replies per tweet	0.228	0.060	0.279	-0.094	-0.025
Hashtags per tweet	-0.114	0.038	-0.040	-0.024	-0.037
Media per tweet	0.026	-0.043	-0.152	-0.060	-0.132
Followers/Following	-0.029	0.043	0.018	0.019	-0.005

Table 4: Correlation between character traits and non-language data. Shaded cells indicate correlation coefficients that are significantly different from 0, where $p < 0.05$.

CHAPTER 5:
Graph Database Storage

After calculating the personality traits for each user, all of the data was then stored in a graph database to allow for easier access to the data and more complex data analysis. This chapter explains the model used to represent the data in a graph database, and identifies some of the questions that can be answered by querying the data.

5.1 Graph Database Model

The graph database program used to store the data from this research is Neo4j. As discussed in Section 2.3, Neo4j stores data as either a node, a relationship, or a property of a node or relationship. The overall model used to store this data is shown in Figure 15 and explained in more detail in this section.

5.1.1 Labels

The following labels were used to group the node data:

- User: a node to represent a user
- Tweet: a node to represent a tweet
- Hashtag: a node to represent a hashtag
- Location: a node to represent a latitude and longitude
- Characteristic: a node to represent one of the five personality characteristics in the Five Factor Model as described in Section 2.1
- Timeline: a single node used to organize the date and time references as described in Section 5.1.5
- Year: a node to represent a year from 2008 to 2015
- Month: a node to represent each of the months of a year
- Day: a node to represent each day of a month

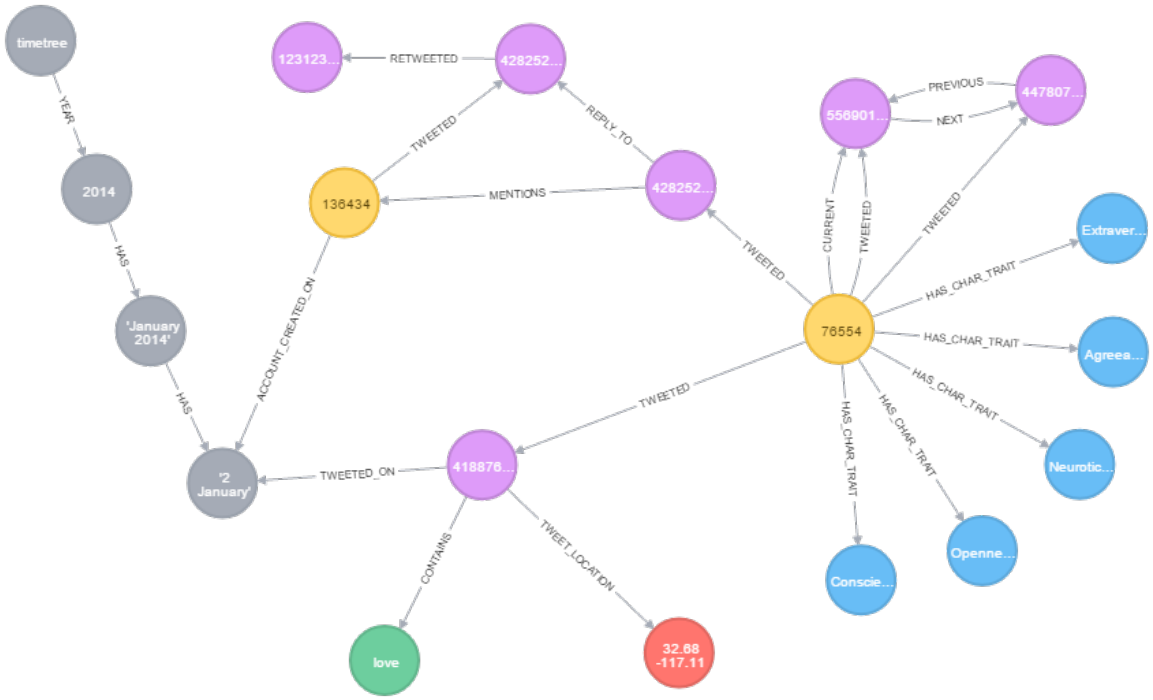


Figure 15: Visual representation of Graph Database Model for Twitter Data. Purple nodes represent Tweets, yellow nodes represent Users, blue nodes represent Characteristics, gray nodes represent the time tree, the green node represents a Hashtag, and the red node represents a Location.

5.1.2 Properties

Properties are additional data stored with a node or relationship; each instance of a node type may have any or all of these properties. A Location node has the properties of latitude and longitude. Each **ACCOUNT_CREATED_ON** and **TWEETED_ON** relationship has a property of time, and the relationship **HAS_CHAR_TRAIT** has a property defining where that User falls with that character trait on a scale from zero to one, using the calculations from Section 3.3. A User node has properties as listed in Table 5; a Tweet node has properties as listed in Table 6. The values of these properties come from Twitter as described in Section 2.2.1.

5.1.3 User Relationships

User nodes can be connected to other nodes in the following relationships:

id	screen_name
name	default_profile
default_profile_image	description
favourites_count	followers_count
friends_count	geo_enabled
lang	listed_count
location	protected
statuses_count	time_zone
url	verified

Table 5: List of properties of a User node.

id	screen_name
favorite_count	in_reply_to_screen_name
in_reply_to_status_id	in_reply_to_user_id
lang	sensitive
retweet_count	text
type	url

Table 6: List of properties of a Tweet node.

- User **TWEETED** a Tweet
- User **HAS_CHAR_TRAIT** Characteristic
- User **ACCOUNT_CREATED_ON** a Day
- User's **CURRENT** Tweet
- Tweet **MENTIONS** a User

Figure 16 provides a graphical representation of all of the possible relationships for a User node.

5.1.4 Tweet Relationships

Tweet nodes can be connected to other nodes in the following relationships:

- Tweet was **TWEETED_ON** a Day
- User **TWEETED** a Tweet
- User's **CURRENT** Tweet

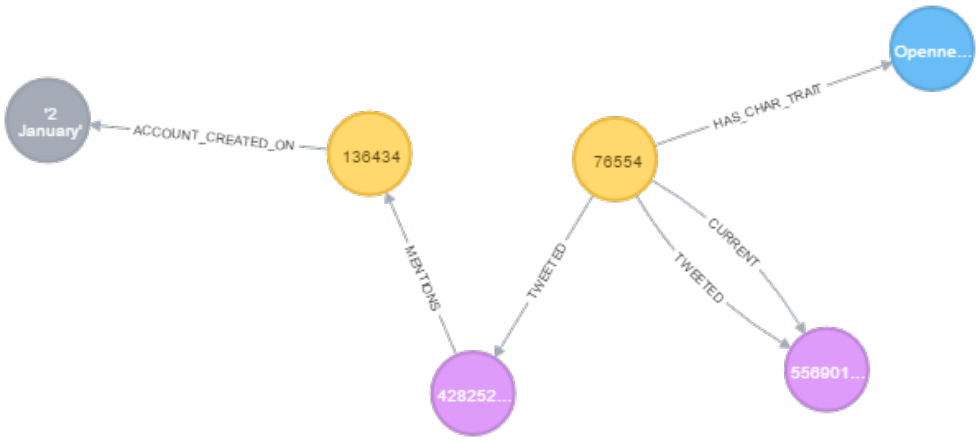


Figure 16: Neo4j output showing all of the possible ways a User can be connected to another node.

- Tweet **MENTIONS** a User
- Tweet **CONTAINS** a Hashtag
- Tweet is connected to a User's **PREVIOUS** Tweet
- Tweet is connected to a User's **NEXT** Tweet
- Tweet **RETWEETED** another Tweet
- Tweet was in **REPLY_TO** another Tweet
- Tweet has a **TWEET_LOCATION** of Location
- Tweet **CONTAINS** a Hashtag

Figure 17 provides a graphical representation of the possible relationships for a Tweet node.

5.1.5 Time Relationships

Years, Months and Days nodes are connected to each other using the following relationships:

- User **ACCOUNT_CREATED_ON** a Day
- Tweet was **TWEETED_ON** a Day
- Timeline contains the **YEAR** Year
- Year **HAS** a Month
- Month **HAS** a Day

Each user profile and tweet has a date and time associated with its creation. The dates were built using a timeline tree, as depicted in Figures 18–21. Each year represented in the data,

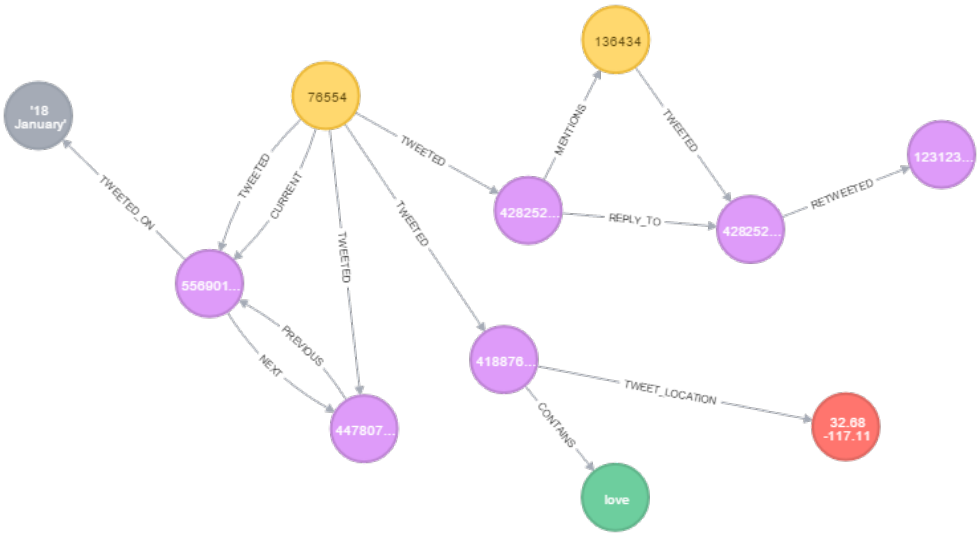


Figure 17: Neo4j output showing all of the possible ways a Tweet can be connected to another node.

from 2008 to 2015, has a Year node, and each Year node has its own set of 12 Month nodes. Each Month node has its own set of Day nodes. Users and Tweets are linked to Days with an **ACCOUNT_CREATED_ON** or **TWEETED_ON** relationship with the time of creation stored as a property of the relationship.

5.2 Querying the Data

Once all the data has been imported into the database, it can be queried to find answers about the data. Queries are written using the language Cypher as described in Section 2.3.

One simple query would be to identify which users have a high level of Conscientiousness, which has a strong correlation with job performance [6]. The Cypher query to answer that question is:

```
MATCH (u:User)-[r:HAS_CHAR_TRAIT]->(:Characteristic
 {name:"Conscientiousness"})
WHERE r.level > 0.7
RETURN u
```

Researchers also showed that successful adjustment to the military lifestyle was correlated

Figure 18: Diagram of a timeline tree in Neo4j, showing the connections from the overall Timeline node to a User node.

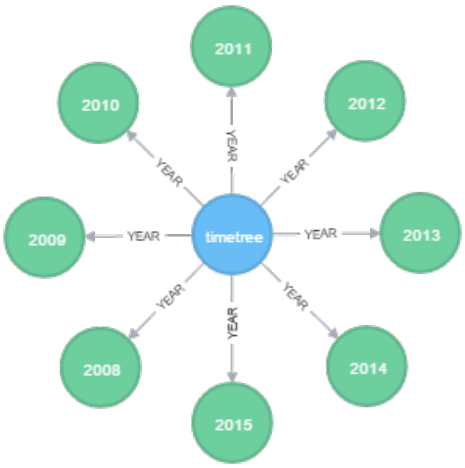


Figure 19: Diagram of the connections from the Timeline node to the Year nodes in Neo4j.

with higher levels of Extroversion and Openness to Experience and lower levels of Neuroticism [15]. The Cypher query to search the database to identify how many of the Navy users meet that standard is:

```
MATCH (u:User)-[r:HAS_CHAR_TRAIT]->(:Characteristic
{name:"Extraversion"})
WHERE r.level > 0.7
MATCH (u)--[s:HAS_CHAR_TRAIT]->(:Characteristic {name:"Openness
 to Experience"})
WHERE s.level > 0.7
MATCH (u)--[t:HAS_CHAR_TRAIT]->(:Characteristic {name:"Openness
 to Experience"})
WHERE t.level < 0.4
RETURN count(u)
```

Although this research focused on personality traits, there are many more questions that can be asked about the data once it is in a database. One interesting question would be to identify

Figure 20: Diagram from Neo4j depicting the relationships between a Timeline node, a single Year node, and its respective Month nodes.

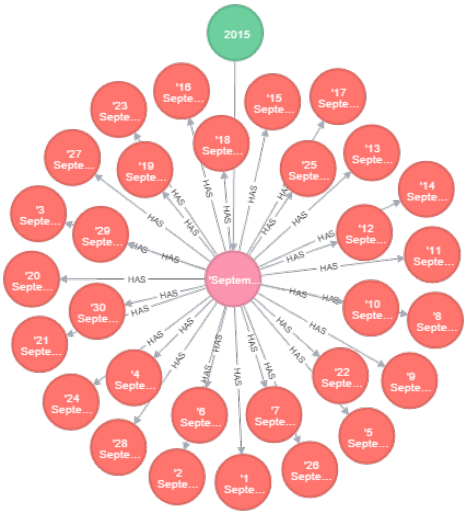


Figure 21: Diagram from Neo4j depicting the relationships between a Year node, a single Month node, and its respective Day nodes.

the users who have interacted with the official U.S. Navy Twitter account, @USNavy, by retweeting a tweet originally posted by the U.S. Navy account. The Cypher query to identify these users is:

```
MATCH (u:User {scr_name:"USNavy"})-[:TWEETED]->(t:Tweet)
MATCH (t)<-[:RETWEETED]-(v:Tweet)<-[:TWEETED]-(w:User)
RETURN w
```

Because a user can tag their tweets with a location, that information can be extracted provide a view of where Sailors are tweeting from. The Cypher query to identify which users are geotagging their tweets and all of the locations is:

```
MATCH (l:Location)<-[:TWEET_LOCATION]-(:Tweet)
 <-[:TWEETED]-(u:User)
RETURN l, u
```

Storing the data in a database allows both more complicated queries related to the initial research question as well as a broader range of queries on the data.

THIS PAGE INTENTIONALLY LEFT BLANK

CHAPTER 6:
Conclusion and Future Work

This chapter presents the overall conclusions of this research as well as recommendations for future work in both the use of Twitter activity to determine personality and the use of personality information to determine fitness for Naval service.

6.1 Conclusions

This research was conducted to answer two questions:

- Can the personality characteristics of well-performing Navy personnel be determined based on their use of the Twitter social media platform?
- Can useful information be determined about a user's personality and activity in order to differentiate Navy Twitter users from the general Twitter user population?

The finding of this research is that it is possible to determine the personality characteristics of Navy personnel based solely on textual analysis of their Twitter posts. With the exception of the few anomalies discussed in Section 4.2, a user's level of each of the personality traits of the Five Factor Model was successfully calculated.

On the other hand, this research also discovered that determining a user's personality does not provide enough useful information to differentiate between Navy users and non-Navy users. The method of calculating a user's personality traits as explained in Section 3.3 did not permit the comparison of averages between the non-Navy population studied in [10] and the Navy population used in this research, and little other useful information could be determined from the statistics of the Navy population. There was also almost no correlation between a user's personality and their Twitter activity, with only one non-language factor having a moderate level of correlation with a personality characteristic.

Although there was some useful information in the results, the primary conclusions of this research is that using textual analysis and the correlation data from [10] is insufficient to identify specific traits that make Navy personnel stand out on Twitter.

6.2 Future Work

Despite the finding that this method of simple textual analysis is insufficient to use as the basis of a model for identifying future Navy recruits, developing a social media-based model for Navy recruitment is still an important research area. There are several ways that further research in this area can be continued.

The first recommendation for future work is to have each of the users in the test population take a previously validated personality test to determine his or her levels of each personality characteristic. This implementation, although more difficult and resource-intensive than the method used in this research, would provide a stronger basis for comparison against the findings in [10] without the weakness of having to use the mean and standard deviation from that work. This might eliminate the problem where the two populations have the exact same mean for each of the traits, which would allow more useful information to be determined from the means. This method would also allow the use of a personality model other than the Five Factor Model.

Another recommendation for future work in this area is to use Twitter data from a population of well-performing Navy users, poorly-performing Navy users, and a similar group of non-Navy users in order to build a classifier that can determine which of these categories a user belongs to. This classifier could then be used to determine whether another user should be in the Navy–that is, if the user shows similar characteristics to those who have succeeded in the Navy. This classifier would be a vital part of a social media-based recruiting tool.

Further research should also be conducted to determine what the best personality characteristics are for different jobs in the Navy. For example, it seems likely that the personalities of those who succeed in jobs such as Information Systems Technician, Steelworker, and Commanding Officer of a ship are quite different. Having the information about different jobs would enable recruiters to target potential recruits with exactly the characteristics needed for the open positions.

Beyond just Twitter or other social media platforms, research should be conducted into the creation and validation of a personality-based assessment for entrance into the Navy or for future promotions. The U.S. Army has been administering the Tailored Adaptive Personality Assessment System (TAPAS) to new recruits at Military Entrance Processing

Stations since 2009, but not actually using it to screen out recruits [21]. Studies following the tested recruits have shown that those who had poor scores on TAPAS have had generally had poor performance in the Army, thus validating its results [21]. The U.S. Navy should begin to use this test to collect data on its validity for Navy personnel before using it as a general screening method at recruiting stations in order to identify those people who are not a good fit for Naval service.

THIS PAGE INTENTIONALLY LEFT BLANK

List of References

[1] A. Perrin, "Social media usage: 2005-2015," Pew Research Center, Tech. Rep., October 2015 2015. [Online]. Available: http://www.pewinternet.org/2015/10/08/2015/Social-Networking-Usage-2005-2015/

[2] "Social media study findings: Media usage and habits among youth ages 16 to 24," Joint Advertising, Marketing Research and Studies, Tech. Rep., 2012.

[3] "GWI social summary," Global Web Index, Tech. Rep., 2015. [Online]. Available: http://insight.globalwebindex.net/social

[4] *Navy recruiting facts and statistics*. Navy Recruiting Command [Online]. Available: http://www.cnrc.navy.mil/facts-and-stats.htm

[5] *Navy Recruiting Manual–Enlisted*, COMNAVCRUITCOMINST 1130.8J, Navy Recruiting Command, Millington, TN, 2011. [Online]. Available: http://www.cnrc.navy.mil/Publications/Directives/1130.8/1130.8J_VOL%20I_Recruiting%20Operations-CH8.pdf

[6] C. Cooper and L. Pervin, *Personality: Critical Concepts in Psychology*, ser. Critical Concepts in Psychology. Routledge, 1998. [Online]. Available: https://books.google.com/books?id=wC6bNZiFq5MC

[7] K. Lee and M. C. Ashton, *The H Factor of Personality*, 2nd ed. Waterloo, Ontario, Canada: Wilfrid Laurier University Press, 2012.

[8] S. J. Gerras, *The Big Five personality traits: A primer for senior leaders*, 2014. [Online]. Available: http://www.carlisle.army.mil/orgs/SSL/dclm/pubs/Big%20Five%20Personality%20Primer%20for%20Senior%20Leaders.pdf?pubID=1179

[9] P. T. Costa Jr and R. R. McCrae, "Domains and facets: Hierarchical personality assessment using the revised NEO personality inventory," *Journal of Personality Assessment*, vol. 64, no. 1, pp. 21–50, 1995.

[10] J. Golbeck, C. Robles, M. Edmondson, and K. Turner, "Predicting personality from Twitter," in *Privacy, Security, Risk and Trust (PASSAT) and 2011 IEEE Third International Conference on Social Computing (SocialCom)*, University of Maryland, College Park. IEEE, 9-11 Oct 2011 2011, pp. 149–149–156. [Online]. Available: http://ieeexplore.ieee.org/xpls/icp.jsp?arnumber=6113107

[11] *Twitter API overview*. [Online]. Available: https://dev.twitter.com/overview/api

[12] *Twitter Firehose vs. Twitter API: What's the difference and why should you care?* (2013, Jun. 25). BrightPlanet [Online]. Available: http://www.brightplanet.com/2013/06/twitter-firehose-vs-twitter-api-whats-the-difference-and-why-should-you-care/

[13] I. Robinson, J. Webber, and E. Eifrem, *Graph Databases: New Opportunities for Connected Data*, 2nd ed. Sebastopol, CA: O'Reilly Media, Inc, 2015.

[14] J. Pennebaker, R. L. Boyd, K. Jordan, and K. Blackburn, "The development and psychometric properties of LIWC2015." The University of Texas at Austin, Austin, TX, 2015.

[15] R. D. de Jong, H.C.M. van Eck, and K. van den Bos, "The Big Five personality factors, leadership, and military functioning," *Personality Psychology in Europe*, vol. 5, pp 216-221, 1994.

[16] F. Mairesse and M. Walker, "Words mark the nerds: Computational models of personality recognition through language." [Online]. Available: http://www.researchgate.net/profile/Marilyn_Walker2/publication/228769720_Words_mark_the_nerds_Computational_models_of_personality_recognition_through_language/links/0c96051f0266fc08c1000000.pdf

[17] F. Mairesse, M. A. Walker, M. R. Mehl, and R. K. Moore, "Using linguistic cues for the automatic recognition of personality in conversation and text," *Journal of Artificial Intelligence Research*, vol. 30, pp. 457–457–500, 2007. [Online]. Available: http://jair.org/media/2349/live-2349-3562-jair.pdf

[18] J. Golbeck, C. Robles, and K. Turner, "Predicting personality with social media," in *CHI'11 extended abstracts on human factors in computing systems*. ACM, 2011, pp. 253–262.

[19] C. Wagner, S. Asur, and J. Hailpern, "Religious politicians and creative photographers: Automatic user categorization in twitter," in *2013 International Conference on Social Computing (SocialCom)*. IEEE, 8-14 Sep 2013 2013, pp. 303–310. [Online]. Available: http://ieeexplore.ieee.org/xpl/articleDetails.jsp?arnumber=6693346

[20] P. M. Gillen, "Real-time detection of operational military information in social media," M.S. thesis, Dept. Comp. Sci., Naval Postgraduate School, Monterey, CA, 2015.

[21] F. Drasgow, S. Stark, O. S. Chernyshenko, C. D. Nye, C. L. Hulin, and L. A. White, "Development of the Tailored Adaptive Personality Assessment System (TAPAS) to support Army personnel selection and classification decisions," DTIC Document, Tech. Rep., 2012.

Initial Distribution List

1. Defense Technical Information Center
   Ft. Belvoir, Virginia

2. Dudley Knox Library
   Naval Postgraduate School
   Monterey, California